R&D MANAGEMENT

Intellectual property reassembly: a novel approach to evaluate R&D collaboration outcomes

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Research and development (R&D) collaboration outcomes have usually been evaluated based on the magnitude of outputs, such as new products, patenting, or productivity growth. However, they have yet to be evaluated based on the various directions of mutual learning between collaborators, which have a long-term impact on the post-partnership technology development of the collaborators. This study proposes a framework that evaluates intellectual property (IP) reassembly, which indicates how a focal firm produces new IP based on its learnings from its R&D partnership, as a novel approach to evaluate R&D collaboration. The proposed approach estimates the degree to which IP reassembly (a focal firm's independent patent applications drawing on co-patents) occurs in the following directions: exploitation of, exploration beyond, or complementary to the pre-partnership capabilities of each collaborator. Within the framework, a focal firm's performance can be compared to that of its partner. The proposed framework is illustrated and validated using the case of partnership between Samsung SDI and BOSCH (2008–2012) in their battery development. We discuss implications for contract design, partnership boundaries, and performance evaluation in the context of R&D collaboration.

1. Introduction

With the increasing attention to open innovation in the last few decades (Chesbrough, 2003; Bogers et al., 2017), research and development (R&D) collaboration for developing new technologies has been widely studied. Many researchers and practitioners have been interested in understanding factors that affect successful R&D collaboration (West et al., 2014). Therefore, various dimensions, such as productivity growth (Belderbos et al., 2004), sales from new products or services (Belderbos et al., 2015), product or process innovation (Maietta, 2015), and the number of patent applications (Huang and Yu, 2011), have been used to measure partnership outcomes.

However, most previous measures of such R&D collaboration outcomes have relied on the magnitude of a particular outcome dimension, such as sales, productivity, or patenting, while ignoring *mutual learning* in the partnership. The principal outcomes of R&D collaboration are technological capabilities, which are intangible. Unlike tangible assets, a focal firm's technological knowledge and skills unintentionally or intentionally spill over to the partner firm (and vice versa) during their collaboration (Hottenrott and Lopes-Bento, 2016; Haskel and Westlake, 2017). This knowledge spillover affects the evolution of the collaborating parties' technological capabilities, continually influencing their subsequent technology development post-partnership (Granstrand, 1999; Bahemia et al., 2018). Moreover, because this knowledge spillover is bidirectional, a firm's collaboration performance can be adequately understood when compared with that of its partner firm – that is, what the partner firm has learned.

Given these features of mutual learning during collaboration, whether the existing measures of R&D collaboration performance properly capture the details of *what has actually been acquired* from relationship comes into question. Oversimplified performance measures can mislead our understanding of a successful R&D collaboration. Moreover, in practice, inadequate evaluation of what an organization has gained from the partnership can lead managers to make inappropriate future decisions. In light of this background, this study provides a new perspective and framework for evaluating R&D collaboration outcomes. Our evaluation considers not only the quantity of certain performance dimensions but also the various *directions* of mutual learning.

Due to the path-dependent nature of organizational learning (Nelson and Winter, 1982; March, 1991), a focal firm's technology development post-partnership is likely to substantially draw on its previous experience – encompassing the experience both during and before a particular partnership. Given this feature, our approach addresses the following essential yet neglected questions in evaluating collaboration outcomes: In what direction has a focal firm internalized technological capabilities through collaboration? (Is it familiar, new, or complementary to itself or the partner?) To what extent has a focal firm learned from the key capabilities of its partner firm? To what extent have the learning outcomes of a focal firm outperformed or underperformed those of its partner firm?

To address these questions, the proposed framework evaluates a focal firm's R&D partnership performance based on its knowledge creation measured by the direction of the firm's independent knowledge production affected by collaboration outputs (hereafter, such knowledge creation is referred to as *intellectual property (IP) reassembly*[1]). The knowledge that a focal firm relies on to independently create new technology can reflect the specific direction of capabilities that the firm has acquired from the partnership. For instance, if learning from the partnership includes capability acquisition relatively new to a focal firm, its subsequent knowledge creation may include the newly acquired technological components building on the collaboration outcomes. Alternatively, if a firm successfully absorbs its partner's key capabilities, its subsequent independent knowledge production may rely on outcomes related to its partner firm's existing key capabilities. Therefore, considering the detailed directionality of learning provides valuable information for evaluation, extending beyond simple existing performance measurements.

To achieve this, we devise a novel approach based on the patent citation information, which has been widely used to quantify technological learning and knowledge flow (e.g., Katila and Ahuja, 2002; Gomes-Casseres et al., 2006). Although patent data incompletely present a firm's knowledge base, they have been regarded as valuable and almost the only public information about technological details, which even reflect some publicly unavailable parts of the firm's capabilities (Hicks, 1995). We illustrate the proposed framework using an R&D collaboration between Samsung SDI and BOSCH in developing battery technology used in electric vehicles. Their partnership started in 2008 and ended around 2012, as their strategic goals diverged. They produced approximately 3,000 mutually accessible co-patents[2] throughout the partnership and continued their independent technology development post-partnership. This case provides a relevant empirical context to illustrate the proposed framework. We validate how our framework reflects reality based on the interviews and written evidence provided by relevant experts.

This study makes significant contributions to both R&D management practice and literature. Firstly, we provide perspective and guidance for managers in evaluating R&D collaboration performance. Our results highlight not only the importance of but also the necessity for continuously monitoring the portfolio of collaborative activities and making changes as needed. Our framework may serve the interests of experts who need to monitor the medium- and long-term firm-level outcomes driven by R&D partnerships. Second, the perspective suggested by this study can be employed to enhance the design of contracts before entering into partnership. Our insights can be useful in determining what to co-create to maximize the benefits from R&D collaboration, considering the potential risks of unintended knowledge spillover given the partner firm's pre-partnership capabilities. Finally, the new perspective proposed in this study should be taken into account in future research that involves measuring the R&D collaboration performance at the firm level. In addition to the conventional measurements, our approach can offer a multi-dimensional perspective that considers various directions of learning through the relationship.

The remainder of this paper is organized as follows. Section 2 reviews the background literature on R&D collaboration and IP reassembly. Section 3 details the framework. Section 4 presents the results of the case study on Samsung SDI and BOSCH. Section 5 discusses the study's key implications and avenues for future research.

2. Conceptual background

2.1. *Evaluation of R&D collaboration outcomes*

Partnerships that co-create intangibles and tangibles are fundamentally different. This is mainly because defining the boundaries of inter-organizational interaction for co-creating intangibles is not straightforward. Therefore, collaborators exchange knowledge within and outside the planned boundaries, including those that are not meant to be shared. Such unintended knowledge spillover frequently occurs, especially when collaborators work together to create something new (Lane and Lubatkin, 1998). Technological knowledge and capabilities can be transferred from one collaborator to another during partnership, even without a formal IP ownership transfer.

Moreover, knowledge spillover is irreversible. A focal firm cannot take back its unintentionally spilled know-how and capability. Such irreversibility is another unique characteristic of intangibles in comparison with tangible assets (Granstrand, 1999). Mutual learning outcomes from an R&D partnership involving within-boundary (intentional) and outside-boundary (unintentional) knowledge spillover remain post-partnership and continuously impact their independent knowledge production (Bogers, 2011; Terhorst et al., 2018).

Therefore, conventional measures, such as improvements in sales, new products, and patent applications, have limitations in comprehensively capturing what collaborators gain through R&D partnerships. Existing measures are mainly based on short-term changes in performance outcomes. However, identical values for a specific outcome dimension can be interpreted differently depending on learning directions. For example, a similar increase in the number of a focal firm's patent applications post-partnership can have different implications depending on what the firm has learned from the partnership. The focal firm can simply obtain capabilities that incrementally improve its existing knowledge. Conversely, the focal firm can learn something entirely new to itself or key know-how of the partner firm. The latter case can be interpreted as more meaningful learning outcomes than the former because the major motivation for R&D partnership is not simply increasing efficiency but acquiring complementary or new capabilities (Katz and Martin, 1997).

Similarly, at the product level, the number of new products produced post-collaboration by a focal firm can have different meanings depending on its level of association with the firm's existing product portfolio. Some of the focal firm's new products may present slight improvements from their existing products. Others may differ vastly from the existing ones or include salient features newly learned from the partner firm.

In addition, an R&D partnership in which collaborators co-develop a targeted technology is not a unidirectional or hierarchical relationship but a bidirectional or horizontal relationship including mutual learning. Therefore, a firm should evaluate its R&D collaboration outcomes by considering its partner firm's outcomes. Depending on what a partner has acquired from the relationship, interpretations of what a focal firm has gained can be different. The ex-partner firm of a focal firm can be its future competitor in areas where they co-developed certain capabilities through their old partnership (Bengtsson and Kock, 2014). If a partner firm gained significant capabilities in an area where the focal firm targets to specialize based on the partnership outcomes, the focal firm must secure its unique complementary assets to be able to capture value from the new investment (Teece, 1986). Accordingly, it is essential to consider a partner firm's learning directions when one evaluates R&D collaboration outcomes.

To sum up, we need to consider the unique nature of intangibles and reflect the mutual learning process when evaluating R&D partnership. This approach will help us conduct a more comprehensive assessment to judge whether a focal firm has acquired meaningful capabilities from the partnership.

2.2. *IP reassembly based on the R&D collaboration outputs*

This study captures the learning directions using the features of independently produced technologies affected by the jointly produced outputs during the partnership. This approach is associated with a recent discussion on how collaborators can successfully close the open innovation by disassembling and reassembling technological capabilities gained through a partnership (e.g., Granstrand and Holgersson, 2014; Barbic et al., 2021). Although open innovation scholars have extensively investigated how R&D partnerships can be effectively started and managed, the literature on successful closing of the relationship and post-partnership knowledge management is sparse.

Collaborating firms have incentives to perform R&D outside the specified boundaries of knowledge sharing, during and after the partnership. Hence, a focal firm can strategically reuse capabilities obtained from the collaboration to build and expand its technological capabilities, called *IP reassembly*. Serendipities can emerge from this process because the knowledge required to achieve the common goal of collaboration can unexpectedly contain ideas needed to find solutions for other problems. Thus, to evaluate the performance of R&D collaboration by considering the IP reassembly, we must first conceptually understand the difference between knowledge possessed by collaborators pre-, during, and post-partnership.

To reflect this, we rely on the concepts of *background*, *foreground*, *side-ground*, and *post-ground* knowledge discussed in the recent literature on how to close the open innovation (e.g., Bader, 2007; Granstrand and Holgersson, 2014; Horeth, 2021). Each concept indicates different areas of firm-level knowledge in R&D collaboration process (see Figure 1). Background knowledge indicates both collaborators' pre-partnership knowledge. Foreground knowledge corresponds to the collaborators' jointly produced knowledge. Side-ground knowledge refers to the collaborators' independent knowledge production *during* partnership based on foreground knowledge. Lastly, post-ground knowledge refers to the collaborators' *post*-partnership independent knowledge production building on foreground knowledge.

The sum of the side-ground and post-ground knowledge corresponds to the *IP reassembly* in the sense that it builds on the co-produced outputs but is generated independently by each collaborator. Foreground knowledge can potentially shape a direction in which a firm's side-ground knowledge and post-ground knowledge are created. The degree to which a firm's IP reassembly relies on the co-produced outputs (i.e., foreground knowledge) that are familiar, new, or complementary to its (or its partner's) existing knowledge reveals the details of the capabilities acquired from the partnership.

3. A proposed approach: unfolding the IP reassembly process

Our approach evaluates the directions of IP reassembly, that is, the degree to which a focal firm can independently create technologies based on the collaboration outputs. In particular, we measure the extent to which the IP reassembly is based on foreground knowledge having certain features – familiar, new, or complementary to the focal firm's or partner firm's pre-partnership capabilities (i.e., background knowledge) (see Figure 1 and Section 2.2).

Following previous studies (e.g., Belderbos et al., 2014), we use patents co-owned by collaborators (hereafter referred to as *co-patents*) to capture the foreground knowledge. Technological outputs of

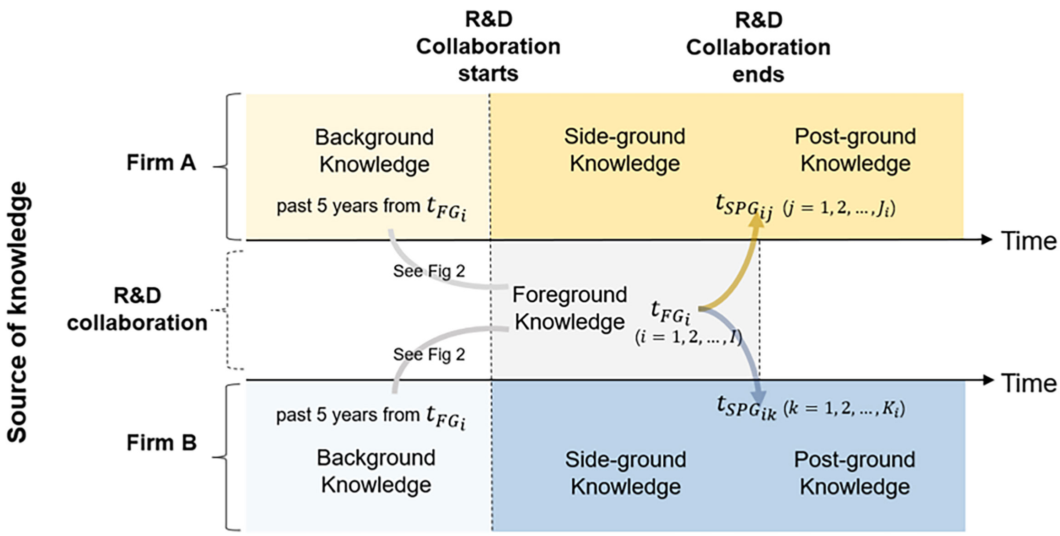

Figure 1. Knowledge types in R&D collaboration. This figure is adapted from Bader (2007) and Granstrand and Holgersson (2014). If Firm A is a focal firm, Firm B is a partner firm (and vice versa). They co-produce foreground patent FG_i at time t_{FG_i} $(i = 1, \dots, I)$. Firms A and B produce side-/post-ground (SPG) patents citing FG_i at times $t_{SPG_{ij}}$ $(j = 1, \dots, J_i)$ and $t_{SPG_{ik}}$ $(k = 1, \dots, K_i)$, respectively. The FG_i-related background knowledge of Firms A and B indicates patents produced by each firm during the past five years from t_{FG_i} (i.e., $t_{FG_i} - 4 \sim t_{FG_i}$).

R&D partnerships are often co-owned by collaborators, though the ownership details can differ across contracts. Although various types of collaboration contracts may exist, restricting the patenting, utilization, and ownership of co-produced technologies, our focus is on sectors where co-patenting is widely employed as a method to protect and access co-produced technologies. Additionally, we focus on the R&D collaborations in which contracts legally allow collaborators to produce and implement subsequent technologies based on the co-patents.[3]

Foreground knowledge is created based on the collaborators' background knowledge (see gray links in Figure 1). Some parts of foreground knowledge can be substantially reliant on a focal firm's background knowledge; other parts can draw more from the partner firm's background knowledge. In addition, some parts of foreground knowledge can include both the overlapping and non-overlapping aspects with a focal firm's (or a partner firm's) background knowledge, implying its potential to complement the firm's existing capabilities (e.g., Mowery et al., 1996).

As reflected in the various linkages between background knowledge and foreground knowledge, each collaborator reaches a unique technological position (combination of firm-specific background knowledge and co-produced foreground knowledge) at the end of the partnership. IP reassembly can differ between collaborators depending on their capabilities internalized from the partnership. Therefore, the foreground knowledge that a collaborator relies on for its independent knowledge production (side-ground and post-ground knowledge) reflects its internalized technological capabilities.

3.1. Dimensions of evaluation

We propose six dimensions capturing different learning directions to evaluate R&D partnership outcomes based on the IP reassembly process (Figure 2). The dimensions capture the extent to which a focal firm's IP reassembly (i.e., side-ground and post-ground knowledge production) relies on foreground knowledge (i.e., co-patents) having the following features: (1) exploitation of a focal firm's background knowledge (Section 3.1.1), (2) exploitation of a partner firm's background knowledge (Section 3.1.2), (3) exploration beyond a focal firm's background knowledge (Section 3.1.3), (4) exploration beyond the partner's background knowledge (Section 3.1.4), (5) complementary to the focal firm's background knowledge (Section 3.1.5), and (6) complementary to the partner's background knowledge (Section 3.1.6).

3.1.1. Exploitation of a focal firm's background knowledge

The first dimension of evaluation is the degree to which a focal firm's IP reassembly draws on foreground knowledge that exploits its pre-partnership capabilities (Figure 2(1)). This dimension is the most expected and relatively low-cost learning direction, given the path-dependent nature of technological learning (Nelson and Winter, 1982; March, 1991). A firm's past experiences generate path dependency, leading it to rely on its prior knowledge bases when scanning, acquiring, and creating new technologies. Accordingly, knowledge that is exploitative of background knowledge likely constitutes a significant proportion of side-/post-ground knowledge production.

However, the high volume of IP reassembly in this area alone does not indicate a gain of the most desirable outcomes because firms collaborate to enjoy synergy rather than simply increase quantity in a repetitive area (Katz and Martin, 1997). That is, when relying solely on conventional measures such as the number of subsequent patent applications,

	Nature of foreground knowledge		
	Exploitation of	Exploration beyond	Complementary to
Focal firm's background knowledge	(1) $Depth_{focal_i} = \frac{\sum_{t=t_i-4}^{t_i} repetition\ count_{focal_{it}}}{total\ citations_i}$	(3) $Scope_{focal_i} = \frac{new\ citations_{focal_i}}{total\ citations_i}$	(5) $Complementarity_{focal_i} = Depth_{focal_i} \times Scope_{focal_i}$
Partner firm's background knowledge	(2) $Depth_{partner_i} = \frac{\sum_{t=t_i-4}^{t_i} repetition\ count_{partner_{it}}}{total\ citations_i}$	(4) $Scope_{partner_i} = \frac{new\ citations_{partner_i}}{total\ citations_i}$	(6) $Complementarity_{partner_i} = Depth_{partner_i} \times Scope_{partner_i}$

Figure 2. Measuring the nature of foreground knowledge (perspective of a focal firm). A focal firm's IP reassembly process is evaluated based on these six measures (1)–(6). The evaluation outcome is compared to that of the partner firm (i.e., the perspective of a partner firm).

the performance evaluation is likely to be biased toward self-exploitation-related outputs, overlooking other potentially valuable directions of learning. Therefore, this first indicator should be supplemented by other dimensions, which will be introduced below.

3.1.2. *Exploitation of a partner firm's background knowledge*

The second dimension of evaluation concerns the extent to which a focal firm's IP reassembly uses foreground knowledge that is reliant on its partner firm's background knowledge (Figure 2(2)). This dimension strongly indicates whether and to what extent a focal firm has absorbed its partner firm's core technological capabilities through the partnership. In other words, a high value of this indicator implies a significant transfer of the partner firm's key technological capabilities to the focal firm. Given that the inter-organizational R&D collaborations primarily aim to absorb deeply embedded knowledge from partners (Hamel et al., 1989), separate measurement for this particular learning direction matters.

In particular, this dimension matters more when a firm engages in (at least potentially) competitive collaboration, which is quite common in high-tech industries (Huang and Yu, 2011). Such spillover of key knowledge during collaboration can be intentional (planned) or unintentional. However, if it was unintentional, the spillover suggests that a partner firm might experience a substantial decrease in its competitiveness because it unexpectedly loses its technological scarcity and uniqueness. For a focal firm, acquiring the partner's key capabilities could lead to significant benefits and opportunities after the collaboration.

Evaluating this second direction of learning differs qualitatively from the evaluation of the first direction (Section 3.1.1) in that the second intentionally excludes the path-dependent learning, focusing instead on the internalization of the partner's key capabilities.

3.1.3. *Exploration beyond a focal firm's background knowledge*

The third dimension of evaluation is the degree to which a focal firm's IP reassembly relies on the foreground knowledge vastly different from its own background knowledge (Figure 2(3)). This indicator captures the extent to which a focal firm has internalized *new-to-the-firm* capabilities from the partnership. Firms tend to rely on exploiting existing capabilities and avoid exploring new areas because searching for and integrating unfamiliar knowledge can be costly.

However, investment in exploring new territory is crucial for maintaining its innovation capability and long-term survival (March, 1991). High values of this indicator imply that a focal firm has extended the boundary of its capabilities into a new territory. Such diversification can increase the likelihood of innovative recombination of knowledge needed to create new technologies in the long run (Nelson, 1959). Therefore, this third dimension measures a different direction of learning from the first two directions.

This direction of learning can include a significant share of overlapping components with the second dimension (Section 3.1.2) in case the new skill acquisition itself is directly related to the partner firm's essential capabilities. However, the third dimension can even cover a broader range of *new-to-the-firm* learning such as the innovative and radical new ideas generated through the partnership, going beyond the acquisition of partner's key capabilities. Hence, the proposed indicators should be collectively considered in the evaluation, as they can complement each other, though they are not mutually exclusive.

3.1.4. *Exploration beyond a partner firm's background knowledge*

The fourth dimension is the extent to which a focal firm's IP reassembly relies on the foreground knowledge vastly different from the partner firm's background knowledge (Figure 2(4)). This indicator's significance depends on the partner firm's capability acquisition in the same area. If the partner firm has also obtained the relevant knowledge, it has gained the critical new capabilities required for its diversification (Garcia-Vega, 2006). Such fields can be one of its future investment targets despite the high risk. If both collaborators invest in this area post-partnership, they are likely to compete against each other. Therefore, the focal firm's high value in this indicator should be differently interpreted, depending on the partner firm's capability acquisition in the same area.

3.1.5. *Complementary to a focal firm's background knowledge*

The fifth dimension is the degree to which a focal firm's IP reassembly draws on the foreground knowledge complementary to its background knowledge (Figure 2(5)). Empirical studies in various contexts of open innovation have provided evidence that a moderate combination of new and old capabilities often results in higher performance than sticking to the entirely unfamiliar or existing capabilities. These include the evidence from the context of mergers and acquisitions (e.g., Makri et al., 2010), alliances (e.g., Mowery et al., 1996), and crowdsourcing (e.g., Afuah and Tucci, 2012).

Such evidence provides a rationale for considering *complementarity* as one of the key dimensions in measuring performance in our context, in conjunction with exploitation and exploration addressed above. While there is no single definition of technological complementarity between two entities, a widely employed concept in the literature suggests that complementarity should entail the co-existence of shared understanding about a certain domain and distinct focused expertise (e.g., Mowery et al., 1996; Makri et al., 2010). Hence, the complementary foreground knowledge in our context should include elements that not only have common features with a firm's background knowledge but also have clearly different focuses.

For the focal firm, technologies obtained in the complementary area can be a highly promising target for future investment. If the focal firm heavily relies on the foreground knowledge complementary to its background knowledge after the partnership, the relevant IP reassembly can be interpreted as highly promising activities.

3.1.6. Complementary to a partner firm's background knowledge

The last dimension of evaluation is the extent to which a focal firm's IP reassembly uses foreground knowledge complementary to the partner firm (Figure 2(6)). This indicator can be informative, particularly when the partner firm has also acquired capabilities in the same area.

Given the usefulness of complementary capabilities discussed in Section 3.1.5, the partner firm that has gained the capability is likely to be in a competitive position in the context of benefiting from the relevant technologies. Therefore, a partner firm that has acquired relevant capabilities is likely to continue to invest in the area post-partnership. A focal firm with a high value of this indicator must be aware that the partner firm can be competitive in this area in the future.

3.2. Measurement

Using patent citation data, Katila and Ahuja (2002) quantified the degree to which a firm's new technology corresponds to the exploitation of (depth of learning) or exploration beyond (scope of learning) its existing capabilities. In addition, the multiplication of the two dimensions, exploitation and exploration, can serve as a proxy for complementary capabilities because the resulting value increases as *both* dimensions attain higher values, as depicted in Figure A1. This measurement well aligns with our definition of complementary capabilities outlined in Section 3.1.5.

Figure 2 summarizes how we quantify the characteristics of foreground knowledge in terms of its relationship with background knowledge by adapting the approach of Katila and Ahuja (2002) to our context. Six indicators described in Section 3.1. are measured for each co-patent (foreground knowledge), demonstrating how they are linked with the background knowledge of each collaborator. Hence, we obtain six continuous values measured per co-patent, each capturing different directions of learning.

As noted in Section 3.1.3, these six indicators are not mutually exclusive but complement each other, depending on the context. For example, the knowledge areas corresponding to the exploitation of a partner's background knowledge (Section 3.1.2) and exploration beyond the focal firm itself (Section 3.1.3) can often overlap. However, this overlap is not always the case because there can be co-patents created in areas that are far from both a focal firm's and its partner's background knowledge. Therefore, the six indicators need to be collectively considered for evaluating mutual learning performance.

The extent to which co-patent i created at t_i exploits focal firm's background knowledge ($Depth_{focal_i}$) is measured as the average frequency at which each backward citation in the co-patent i was repeatedly used in its own background knowledge (Figure 2(1)). Therefore, the sum of repeated citation counts in the focal firm's own background knowledge ($\sum_{t=t_i-4}^{t_i} repetition\ count_{focal_{it}}$) is divided by the total number of backward citations in the co-patent i ($total\ citations_i$). The extent to which co-patent i exploits partner firm's background knowledge ($Depth_{partner_i}$) is calculated by applying the same logic, but considering the partner's background knowledge instead of that of the focal firm (Figure 2(2)).

The degree to which co-patent i explores beyond focal firm's background knowledge ($Scope_{focal_i}$) is measured as the proportion of backward citations in co-patent i that are not used in the focal firm's background knowledge. Hence, the number of co-patent i's backward citations that could not be found in the background knowledge ($new\ citations_{focal_i}$) is divided by the total number of backward citations in the co-patent i ($total\ citations_i$) (Figure 2(3)). The same logic applies to measuring the degree to which co-patent i explores beyond the partner's background knowledge ($Scope_{partner_i}$), but using the partner's background knowledge instead of that of the focal firm (Figure 2(4)).

Finally, given the definition of complementarity between two knowledge components explained in

Section 3.1.5, the extent to which a co-patent is complementary to the focal firm's background knowledge ($Complementarity_{focal_i}$) is computed as a multiplication of $Depth_{focal_i}$ and $Scope_{focal_i}$ (Figure 2(5)). As presented in Figure A1, complementarity score increases when both scope and depth increase together to some extent. Similarly, the extent to which a co-patent is complementary to the partner firm's background knowledge ($Complementarity_{partner_i}$) is computed as a multiplication of $Depth_{partner_i}$ and $Scope_{partner_i}$ (Figure 2(6)).

3.3. IP reassembly process

We aim to estimate the rate at which a collaborator creates patents in side-ground/post-ground knowledge areas linked to the co-patents characterized by the six dimensions that indicate different learning directions. To capture the linkages, we rely on citations from side-ground/post-ground knowledge-related patents (citing) to foreground knowledge-related patents (i.e., cited co-patents).

The estimated coefficient of each learning direction variable presents the rate and direction of IP reassembly process of a firm. For example, a significantly positive coefficient of the variable 'exploitation of partner firm's background knowledge' (i.e., Figure 2(2)) indicates that a focal firm's IP reassembly is likely to be conducted more in areas where a linked co-patent is characterized by its higher exploitation of a partner firm's background knowledge (i.e., the focal firm has successfully internalized the partner firm's existing capabilities).

Given that each co-patent can be used multiple times for a firm's IP reassembly, we need to model the occurrence rate of repeated events. The Cox regressions can be extended to model the hazard rate of repeated events and consider time-varying covariates (Cox, 1972; Kalbfleisch and Prentice, 1980; Cook and Lawless, 2007). Following previous studies (Podolny and Stuart, 1995; Nerkar and Paruchuri, 2005; Jee and Sohn, 2023), we use a recurrent event hazard rate analysis. The equation is specified as follows:

$$\lambda_i(t) = \lambda_0(t)\exp\left(\beta z_i + \gamma x_i(t)\right),$$

where $\lambda_i(t)$ is the rate of patent applications in the side-ground/post-ground knowledge areas that cite co-patent i from time t to $t + dt$; $\lambda_0(t)$ is a baseline rate without assumption about its distribution; z_i is the vector of time-invariant covariates; and $x_i(t)$ indicates the vector of the time-varying covariates.

The time gap between the patent applications that cite co-patent i is used as a dependent variable. The time from a co-patent i's application date to the first independent patent application citing the co-patent i is regarded as the first event; the time periods between subsequent patent applications are sequentially used. Two collaborators can be reflected in a single model using a dummy variable (distinguishing each collaborator's events) interacting with each dimension of evaluation.

4. Case example: Samsung SDI and BOSCH

4.1. Case introduction

We apply the proposed evaluation approach to the case of the R&D collaboration between Samsung SDI and BOSCH. In 2008–2012, they collaboratively developed and manufactured lithium-ion batteries used in electric vehicles. Based on the shared understanding of their complementary capabilities, they established a 50–50 joint venture called SB LiMotive in 2008.

The two firms agreed that Samsung SDI would focus on battery cell development, while BOSCH would concentrate on the battery pack and battery management system (BMS) development. In addition, BOSCH wanted to learn skills concerning battery cell, while Samsung SDI sought to acquire battery pack and BMS skills. Hence, both were allowed to access and exploit the co-produced outputs from the partnership. Although BOSCH's capability before the partnership was less directly related to battery development, it had a robust customer base (i.e., automobile companies) for selling batteries. BOSCH promised to bring Volkswagen as a customer for this partnership, which was an attractive condition for Samsung SDI.[4] In this sense, they both initially had incentives for the joint venture.

Samsung SDI's focus area, the battery cell, was positioned more upstream in the entire value chain compared to that of BOSCH, which focused on battery pack and BMS. However, the joint venture was not for a simple subcontracting relationship, but for a more equal collaborative partnership, enabling access to outputs for both parties and facilitating learning. Since both firms' inputs were necessary for producing and commercializing final battery products, synergies were anticipated throughout the collaborative process. Hence, they sent resident employees to each other's R&D center to facilitate collaboration and mutual learning (Sato, 2016). However, their relationship had not evolved positively, ultimately leading to the official end of the partnership in 2012.

4.2. Descriptive analysis

The data show that 3,532 co-patents (1,361 patents at the family level) were obtained from the partnership. To avoid double-counting the same inventions, we analyze the patent data at the patent family level.[5] Collaborators were legally allowed to access the co-patents produced by their partnership.

Figure 3 demonstrates both collaborators' conceptual mapping of background, foreground, and side-ground/post-ground knowledge in the partnership process. If a co-patent i (i.e., foreground knowledge) was created at t_{FG_i}, we regard a collaborator's patent applications (except co-patents) during the past five years from t_{FG_i} as the background knowledge. The five-year setting reflects the assumption in organizational learning literature that, in high-technology sectors, a firm's memory span is less than five years because of the depreciating nature of knowledge (e.g., Argote, 1999). Each collaborator's patent applications citing the co-patent i after t_{FG_i} during and post-collaboration are regarded as side-ground and post-ground knowledge, respectively.

Figure 4 shows the number of patent applications over time in the foreground (purple line) and side-ground/post-ground knowledge areas (yellow line for Samsung SDI and green line for BOSCH). The figure shows to what extent both firms conducted independent knowledge production based on the co-developed technological outputs. Overall, the simple count presented in this figure indicates that BOSCH produced slightly more side-/post-ground patents reliant on foreground knowledge than Samsung SDI did. Our main analysis will deepen this understanding by providing details of mutual learning directions, that is, where and how the learning has occurred.

Before proceeding to the main analysis, we conduct an intermediate descriptive analysis to better understand foreground knowledge. We plot the distribution of co-patents with respect to the six dimensions of our evaluation (Figure 5).

The x-axis and y-axis of Figure 5a indicate the degree to which each co-patent exploits Samsung SDI's and BOSCH's background knowledge, respectively. The minimum value is 0, and a higher value indicates more exploitation. The numbers in each cell indicate the number of patents in the corresponding area. The figure shows that a significant proportion of co-patents rely on the background knowledge of both collaborators to some extent. At the same time, the figure presents the largest share at the lower-left end (both close to 0), which indicates the relative absence of reliance on the background knowledge. The figure also shows that the overall distribution is skewed toward more exploitation of Samsung SDI's background knowledge than that of BOSCH.

The x-axis and y-axis of Figure 5b present the degree to which a co-patent corresponds to the exploration of Samsung SDI's and BOSCH's background knowledge, respectively. This value ranges between 0 and 1, where a larger value indicates more exploration. This figure shows that a significant share of co-patents was produced in areas that are quite far from both collaborators' background knowledge (both close to 1). Additionally, consistent with the observation in Figure 5a, we can observe that the distribution of the co-patents is skewed to the direction farther from BOSCH's

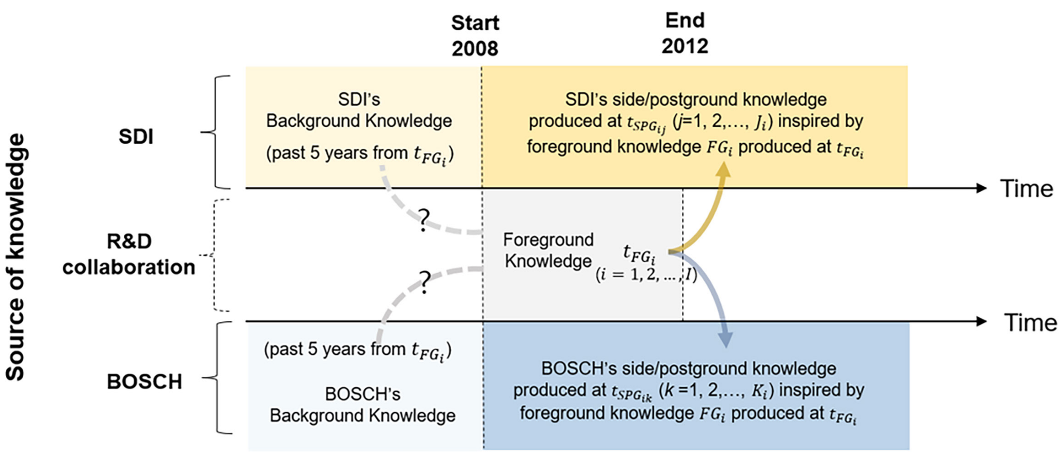

Figure 3. Timeline of IP reassembly: Samsung SDI and BOSCH. Samsung SDI and BOSCH's side-/post-ground (SPG) patents citing a foreground patent FG_i produced at t_{FG_i} are created at $t_{SPG_{ij}}(j=1, \ldots, J_i)$ and $t_{SPG_{ik}}$ $(k=1, \ldots, K_i)$, respectively. The background knowledge related to FG_i for Samsung SDI and BOSCH corresponds to the patents produced by each firm during the past five years from t_{FG_i}.

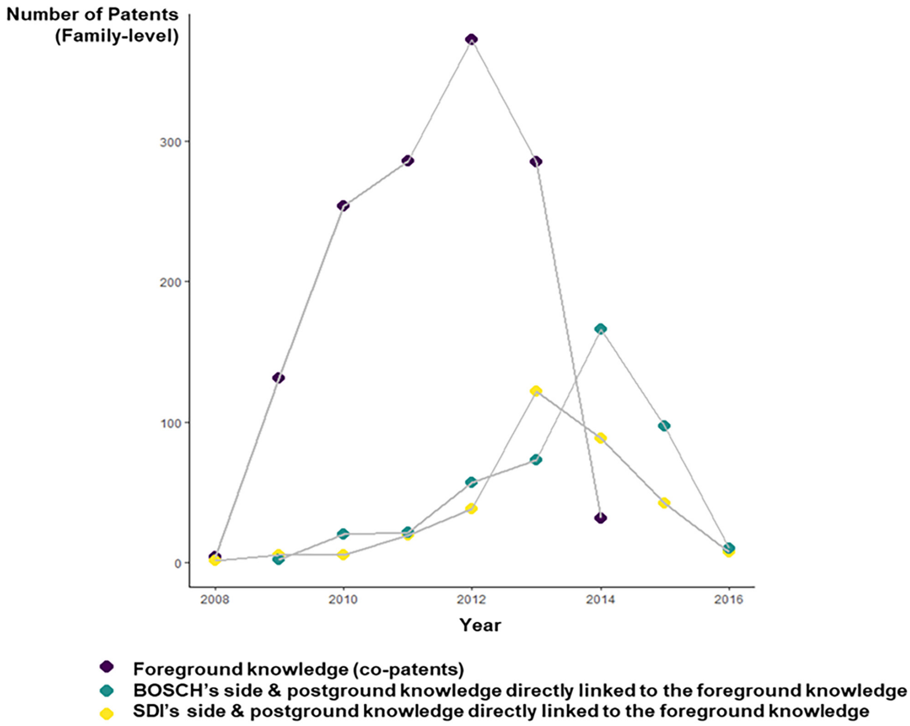

Figure 4. Number of patents (family level) in foreground and side-ground/post-ground knowledge.

background knowledge than Samsung SDI. We also find a big cluster of patents at the bottom left end, indicating the co-patents produced in areas very close to both collaborators' background knowledge (both close to 0).

Lastly, the x-axis and y-axis of Figure 5c indicate the degree to which each co-patent is complementary to the background knowledge of Samsung SDI and BOSCH, respectively. This value is at least 0. Around one-third of co-patents are clustered at the bottom left end (both close to 0), which is the area weakly complementary to both collaborators' background knowledge. The largest share of patents at the bottom left end indicates that satisfying the complementarity conditions is challenging compared to a single direction, either exploitation or exploration. The overall distribution of co-patents is slightly skewed again, presenting the higher number of co-patents in areas complementary to Samsung SDI's background knowledge than BOSCH.

4.3. Main analysis

Table 1 shows the results of estimating the rate at which each collaborator produces side-ground/post-ground knowledge with respect to the six directions described in Section 3.1.

Apart from the main variables indicating learning directions, we control for the variables that could affect the side-ground/post-ground knowledge production citing the co-patents. The variable *age* indicates the time gap between the application date of a co-patent and the date at which the patent application related to side-ground/post-ground knowledge citing the co-patent was made. Given that knowledge diffusion generally follows the S-curve, we control for *age* and *age squared*.

In addition, following previous evidence, we control for *family size*, the *number of applicants* (e.g., Belderbos et al., 2014), and the *number of inventors* (e.g., Alnuaimi and George, 2016). The scope of the patent is captured by the *number of distinct 4-digit CPC* or the *number of patent backward citations* (e.g., Lerner, 1994), which are positively correlated with patent value. Additionally, because it is likely that patent citation happens more frequently as the technology cycle time shortens, we control for the *technology cycle time*, which is the median value of the time gap between the application date of a co-patent and its reference patents.

Model 1 is a baseline model consisting of control variables. The variable *age* of cited co-patent and its *squared* value are both negatively significant, indicating that the age of the cited co-patent has an inverted U-shaped relationship with side-ground/post-ground knowledge, presenting the S-shaped diffusion curve. Consistent with prior evidence, the *number of applicants*, *family size*, and the *number of patent backward citations* are positively related to the side-ground/post-ground knowledge production.

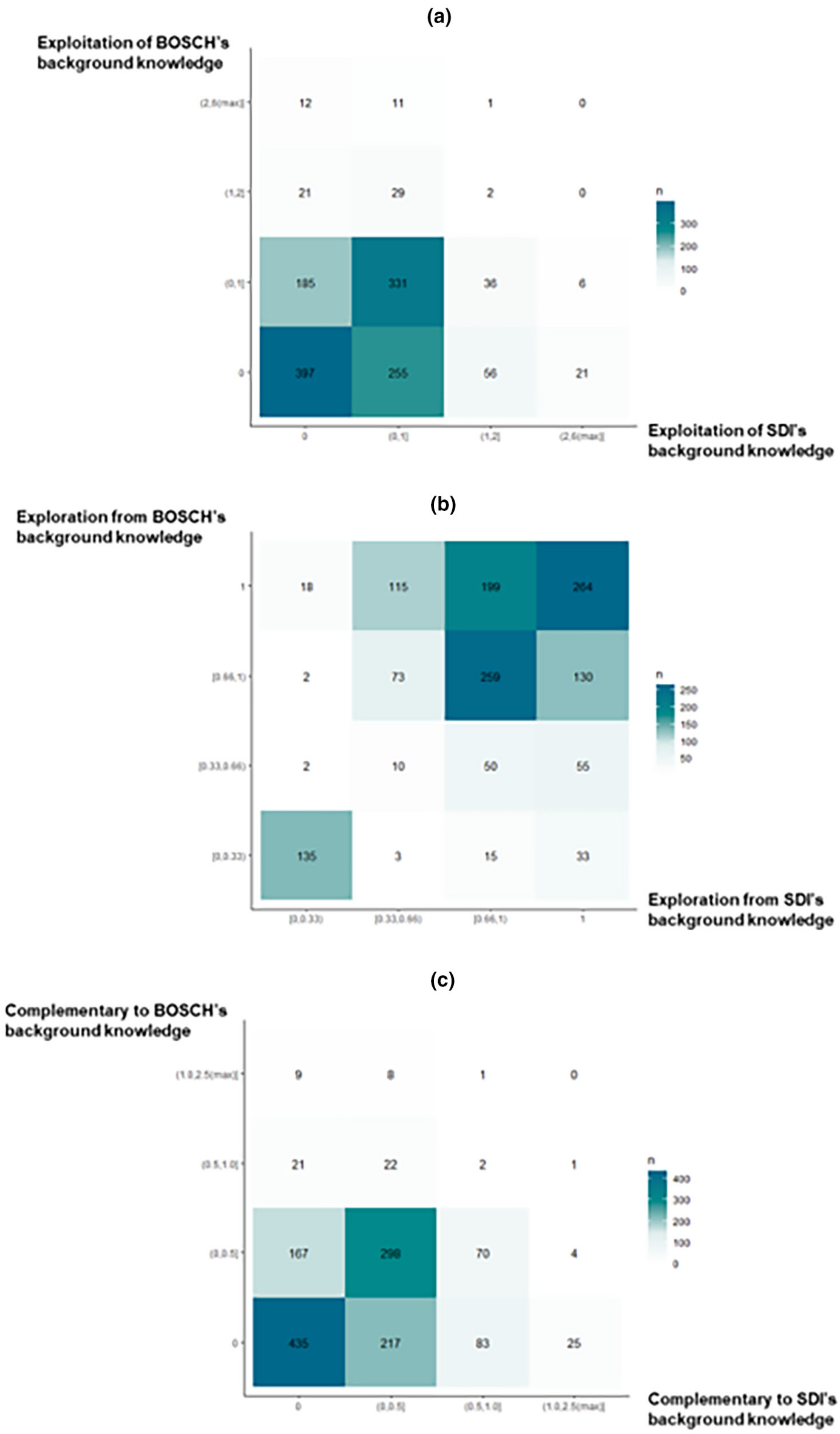

Figure 5. Distribution of foreground knowledge (i.e., co-patent). The numbers in each cell indicate the number of patents (family level) in the corresponding area.

However, the *technology cycle time* and the *number of distinct 4-digit CPC* are not significant in our data and the *number of inventors* is negatively significant.

Models 2, 3, and 4 present the rate of IP reassembly that is exploitation to, exploration beyond, and complementary to the background knowledge (of

Table 1. Results of the Cox regression evaluating the performance of IP reassembly based on the collaboration outputs

	Model 1	Model 2	Model 3	Model 4
Exploitation of SDI's background knowledge × SDI (group dummy 1)		2.24e-01***		
		(6.49e-02)		
Exploitation of SDI's background knowledge × BOSCH (group dummy 2)		2.78e-01***		
		(7.87e-02)		
Exploitation of BOSCH's background knowledge × SDI (group dummy 1)		−2.06e+00***		
		(4.24e-01)		
Exploitation of BOSCH's background knowledge × BOSCH (group dummy 2)		1.69e-01**		
		(9.09e-02)		
Exploration from SDI's background knowledge × SDI (group dummy 1)			−1.13e+00***	
			(2.61e-01)	
Exploration from SDI's background knowledge × BOSCH (group dummy 2)			−1.95e-01	
			(1.93e-01)	
Exploration from BOSCH's background knowledge × SDI (group dummy 1)			3.24e+00***	
			(5.71e-01)	
Exploration from BOSCH's background knowledge × BOSCH (group dummy 2)			−2.07e-01	
			(1.82e-01)	
Complementary to SDI's background knowledge × SDI (group dummy 1)				6.93e-01***
				(1.35e-01)
Complementary to SDI's background knowledge × BOSCH (group dummy 2)				5.91e-01***
				(1.80e-01)
Complementary to BOSCH's background knowledge × SDI (group dummy 1)				−2.27e+00***
				(5.80e-01)
Complementary to BOSCH's background knowledge × BOSCH (group dummy 2)				4.30e-01**
				(2.06e-01)
Group dummy 1 (SDI vs. BOSCH)	−5.73E-02	−2.63e-01***	2.41e+00***	−1.61e-01*
	(7.91e-02)	(1.01e-01)	(5.95e-01)	(1.18e-01)
Age	−4.45e-04*	−3.80e-04	−3.96e-04	−3.23e-04
	(3.21e-04)	(3.08e-04)	(3.12e-04)	(6.49e-02)
Age squared	−7.42e-07***	−7.38e-07***	−7.32e-07***	−7.62e-07***
	(1.28e-07)	(1.24e-07)	(1.26e-07)	(1.25e-07)
Number of applicants	3.52e-01***	3.01e-01***	3.04e-01***	3.01e-01***
	(4.93e-02)	(4.35e-02)	(4.38e-02)	(4.20e-02)
Number of inventors	−2.08e-01***	−1.75e-01***	−1.83e-01***	−1.68e-01***
	(5.66e-02)	(4.91e-02)	(5.07e-02)	(4.66e-02)
Family size	1.48e-01***	1.73e-01***	1.65e-01***	1.56e-01***
	(3.16e-02)	(2.93e-02)	(2.87e-02)	(2.81e-02)
Technology cycle time	9.84e-06	1.23e-05	1.49e-05	1.29e-05
	(1.89e-05)	(1.95e-05)	(2.05e-05)	(1.98e-05)
Number of distinct 4-digit CPC	−5.04e-02	−2.89e-02	−1.45e-02	−3.15e-02
	(6.21e-02)	(5.65e-02)	(5.93e-02)	(4.79e-02)
Number of patent backward citations	8.66e-03***	7.41e-03***	6.97e-03***	6.17e-03***
	(2.34e-03)	(2.27e-03)	(2.27e-03)	(2.26e-03)
Log-likelihood	−11,315.3	−11,241.3	−11,237.3	−11,241.44

Note: Values in parentheses are robust standard errors clustered by firm patent. Group dummy 1 (SDI vs. BOSCH): BOSCH is the reference group. Group dummy 1 is used to evaluate SDI's IP reassembly. Group dummy 2 (BOSCH vs. SDI): SDI is the reference group. Group dummy 2 is used to evaluate BOSCH's IP reassembly.
$*P < 0.1$, $**P < 0.05$, $***P < 0.01$.

Samsung SDI and BOSCH, distinguished by using a dummy variable), respectively.[6]

Model 2 (exploitative direction) in Table 1 shows that the foreground knowledge's reliance on Samsung SDI's background knowledge is positively linked to the rate of its IP reassembly (2.24e-01***), showing a path-dependent reliance on its pre-partnership capabilities. However, the foreground knowledge's reliance on BOSCH's background knowledge is negatively linked to the rate of Samsung SDI's IP reassembly (−2.06e+00***), meaning that Samsung SDI did not absorb the partner's key capabilities. Conversely, the foreground knowledge's reliance on BOSCH's (1.69e-01**) and Samsung SDI's (2.78e-01***) background knowledge is positively linked to the rate of BOSCH's IP reassembly. This result implies that BOSCH not only relies on its own pre-partnership capabilities but also internalizes Samsung SDI's pre-partnership capabilities. To sum up, the results in Model 2 imply that BOSCH managed to significantly absorb Samsung SDI's pre-partnership technological capabilities, while Samsung SDI relatively absorbed less.

Model 3 (explorative direction) shows that the foreground knowledge's exploration beyond Samsung SDI's background knowledge is negatively linked to the rate of its IP reassembly (−1.13e+00***), consistent with the risk-averse nature of organizational learning. The foreground knowledge's exploration beyond BOSCH's background knowledge is positively linked to the rate of Samsung SDI's IP reassembly (3.24e+00***). This is consistent with Model 2, which indicates that Samsung SDI's IP reassembly tends to be far from BOSCH's background knowledge. Conversely, from the perspective of BOSCH's IP reassembly, no significant relationships have been observed in terms of exploration beyond both itself and partner's background knowledge. Summing up, Model 3 indicates that both firms were not able to internalize radically new capabilities that can be regarded as diversification agenda for future business.

Lastly, Model 4 (complementary direction) shows that the foreground knowledge's complementarity to Samsung SDI's background knowledge is positively linked to the rate of SDI's own IP reassembly (6.93e-01***). Similarly, the foreground knowledge's complementarity to BOSCH's background knowledge is positively linked to the rate of BOSCH's IP reassembly (4.30e-01**). These results imply that both firms tried to be benefitted from the foreground knowledge that are complementary to themselves by independent effort of side-ground/post-ground knowledge production. This is in line with our expectation about the complementary learning direction, which is likely to be the next target of investment.

However, the results also show that the foreground knowledge's complementarity to Samsung SDI's background knowledge is positively linked to the rate of BOSCH's IP reassembly (5.91e-01***). By contrast, the foreground knowledge's complementarity to BOSCH's background knowledge is negatively linked to the rate of Samsung SDI's IP reassembly (−2.27e+00***). This implies that BOSCH-internalized skills are complementary to not only itself but also Samsung SDI. However, Samsung SDI was not able to internalize the skills complementary to its partner. Therefore, BOSCH acquired unique complementary technological capabilities, while SDI's complementary capability acquisition was less unique in that partner also significantly learned the relevant skills.

Overall, although the collaborators shared co-patents and continued their own technological development based on the co-patents, the process of IP reassembly observed through multiple directions of learning reveals distinct performances. BOSCH substantially internalized the background knowledge and the complementary capabilities of Samsung SDI acquired during the partnership. However, Samsung SDI was not able to internalize such capabilities of BOSCH and showed a high reliance on its own background knowledge. These are details of mutual learning that would have not been captured if we simply examined the number of patents created by each firm.

4.4. Reflection based on additional qualitative information

Our results are in line with the description in Jun (2020), which is a book about the battery industry, written by a former senior executive from Samsung SDI. The author states that '… *Through SB Limotive, a joint venture established in 2008 between Samsung SDI and BOSCH, BOSCH thoroughly absorbed Samsung SDI's technological capabilities in square type battery cell development. When the joint venture dissolved in 2012, Samsung SDI went through hundreds of millions of dollars of loss and fell into a difficult financial situation. (…) BOSCH is equipped with technological capabilities needed to start an EV battery business, but currently just holding off starting a battery business* …' (p. 70).

Further discussion with the author enabled us to grasp why BOSCH absorbed key technologies from its partner, while Samsung SDI did not achieve the same level of learning. The author says, '*When*

Samsung SDI and BOSCH entered into collaboration, the agreed-upon division of labor was that Samsung SDI focuses on battery cell development, while BOSCH would concentrate on battery pack and battery management system (BMS) development. However, once the collaboration commenced, it turned out that BOSCH lacked the promised capabilities in battery pack and BMS for automotive applications. Therefore, Samsung SDI had to reallocate researchers who had previously worked on the Plasma Display Panel (PDP), which was a withdrawn business by Samsung SDI at the time, to develop pack and BMS technologies. The managers and engineers who involved in this partnership say that Samsung SDI learned nearly nothing from BOSCH in terms of technologies …'.

Another former executive further elaborates on the unequal learning that occurred between the two firms during the partnership (Sato, 2016). The author states, '*… R&D was conducted in both South Korea and Germany. For collaboration, both Samsung SDI and BOSCH sent resident employees to each other's R&D centers. However, after two years, it became apparent that the working conditions were not equal between the two companies, resulting in different learning outcomes. BOSCH's resident employees had access to, observed, and analyzed the development, production, and manufacturing processes of automotive lithium-ion batteries at Samsung SDI. However, Samsung SDI's resident employees had very limited access to BOSCH's R&D sites and were instead confined to performing their duties in an assigned office …*'.

The additional information demonstrates how our evaluation framework reflects reality, particularly in terms of capturing missed learning opportunities for Samsung SDI. In addition, we show how these missed learning opportunities can be linked to long-term impact, specifically the firm's independent knowledge production after the collaboration.

5. Discussion and conclusion

Despite the increasing prevalence of R&D partnerships in high-technology industries, the majority of such attempts fail to yield satisfactory outcomes. One of the main challenges in managing these partnerships is controlling the process of mutual learning. Given that collaborators are constantly motivated to independently develop their own technologies during and after the partnership, the absorption of a focal firm's key capabilities by the partner firm poses a significant risk to the focal firm if such absorption is an unplanned outcome. By contrast, the focal firm's acquisition of new or complementary knowledge or the partner's key capabilities through collaboration could bring significant value to it in the medium and long terms.

Existing methods of evaluating R&D collaboration have limitations in capturing such dynamics of the mutual learning. To address this point, this study proposed a novel approach that evaluates R&D partnerships by considering various directions of mutual learning, shedding light on less-attended aspects of R&D collaboration. The demonstration of the proposed approach clearly reveals the limitations of the existing measures on partnership outcomes. We show how the outcomes that appear seemingly indifferent in a simple quantitative manner can involve totally different routes of learning, shaping different post-partnership behaviors. Our results offer several implications for both R&D management practice and literature.

5.1. *Practical implications*

First, our results point to the importance of improving the design of contracts pre-partnership. The improvement includes the decisions regarding what to co-create through the relationship and the rights to access and exploit the co-created IP. In particular, setting the boundary of knowledge production pre-partnership is crucial because it is unlikely that one collaborator can easily reorient the direction of knowledge co-production once collaboration begins.

Our illustration on the distribution of co-patents (Figure 5) already provides information on whether and to what extent co-produced outputs can be skewed toward a direction advantageous to either party. The skewed distribution of foreground knowledge could subsequently impact the unbalanced production of side-ground/post-ground knowledge between the collaborators (Table 1). Therefore, it is essential to set a reasonable boundary for the expected collaboration outputs and accessibility to the outputs, considering the background knowledge of collaborating parties before they enter into the new relationship. If unintended knowledge spillover to the partner is likely to happen during the partnership, a focal firm should more carefully define boundaries of side-ground/post-ground knowledge production and access allowance before the partnership begins. These boundaries should be explicitly stated in the contract document, formally obligating both collaborators to comply.

Second, we propose a practical tool that helps firms comprehensively evaluate post-partnership utilization of co-produced technologies. Monitoring the collaborative boundary is essential because a firm's internalized capabilities can have a substantial long-term impact on its post-collaboration technology development. As demonstrated by our results, side-ground/post-ground knowledge production based on the co-produced outputs can occur in various directions and be linked to the characteristics of the co-produced outputs. While we illustrate a case in which asymmetric mutual learning is connected to side-/post-ground technology development, one should also note that the full potential utilization of co-produced outputs can depend on additional factors, particularly the absorptive capacity of the firms (Cohen and Levinthal, 1990). Depending on the accumulated level of technological experience and know-how, the way in which co-produced outputs are utilized for future knowledge production can vary. Therefore, it is essential to monitor side-/post-ground knowledge production, going beyond managing the boundary of foreground knowledge. Our framework provides a valuable tool in this regard, helping firms monitor the post-partnership utilization of co-produced technologies.

Lastly, the proposed perspective of evaluation can also be considered in the partner selection stage of R&D collaboration. This phase corresponds to the scanning and selection of an appropriate partner, one of the key aspects in the overall process of managing an R&D partnership (e.g., Lichtenthaler, 2005; Un and Asakawa, 2015). To prevent unintended knowledge spillover, which could threaten a focal firm's market position post-collaboration, the likelihood of knowledge absorption should be a crucial consideration in the partner selection process. By analyzing the existing technological capabilities of candidate partners, a focal firm can evaluate the risk that each candidate absorbs the focal firm's capabilities that are not intended to be shared and envision future trajectories for technology development given the partnership plan.

5.2. Contributions to the literature

In addition to the practical implications, this study also contributes to an interesting perspective on recent scholarly discussions on open innovation (e.g., Granstrand and Holgersson, 2014; Holgersson et al., forthcoming). While many studies on open innovation have investigated performance-related aspects, the existing understanding of IP disassembly and reassembly, which are about disentangling, allocating, and utilizing technological outcomes obtained from R&D collaboration, remains relatively scant. Our results suggest why concluding open innovation is unlikely to be an agenda that can be successfully managed during or post-partnership, but rather an agenda that must be strategically handled pre-partnership.

Another essential contribution to the literature is the suggestion of a new important perspective on measuring R&D collaboration outcomes. Learning directions have typically been considered in qualitative studies (e.g., Bäck and Kohtamäki, 2016) but have been relatively ignored in quantitative research in this field. This study is an early attempt to quantify the various directions of mutual learning during R&D partnerships and their impact post-partnership. Our approach can be considered in future studies that include evaluating the performance of inter-organizational collaboration activities. We provide a complementary evaluation tool to conventional approaches that mostly rely on the simple size of performances. Although our study focuses on an illustration based on a case, the proposed multi-dimensional perspective of measuring performance is valuable as it suggests useful guidance for future studies. The adoption and expansion of the proposed approach will shed new light on our understanding of R&D collaboration, through the testing of hypotheses related to successful collaboration.

5.3. Limitations and future studies

This study is not without limitations, providing avenues for future research. First, as discussed in previous literature (e.g., Prashant and Harbir, 2009), one study cannot address all aspects related to successful collaboration, given that various factors could shape the partnership outcomes. Although we highlight partnership boundary setting and monitoring as important agendas, defining the boundary itself involves uncertainties, as partners may not precisely know the content and quality of the final outcomes at the early stage. Moreover, there can be uncertainties across strategic, structural, or even accidental dimensions that could alter the results of the collaboration.

In a similar vein, it has been documented that firms proficient in IP management, such as IBM, typically treat each collaboration as an individual case (Bader, 2007; Gassmann et al., 2021). In addition, collaborating firms may choose to exclude joint patenting clauses from agreements unless the partnership contributes to mutually beneficial areas, such as technology standard creation, considering the anticipated future costs of negotiations and disputes. Therefore, while our framework can generally be used to evaluate mutual learning in relevant collaboration contexts, it is crucial to also account for how the learning is intertwined with the case-specific factors. These factors encompass aspects such as the distribution of complementary assets, compatibility between partners, and strategic decisions and events specific to the involved firms.

Second, while our definition of IP reassembly focuses on knowledge production with direct links to foreground knowledge, future studies can consider adjusting the boundary of IP reassembly. For example, IP reassembly could encompass side-/post-ground knowledge production that directly cites background knowledge, even when the knowledge lacks a connection to foreground knowledge. This can broaden the scope of IP reassembly, covering a wider range of unintended knowledge spillovers. Alternatively, one can consider defining the boundary of IP reassembly based on similarity-based measures, such as patent text similarity or technology class similarity between foreground and side-/post-ground knowledge, instead of citation linkages. While similarity-based IP reassembly may entail some fuzziness, it could accommodate a broader range of post-partnership technology development that cannot be captured by citation information.

Third, while this study has offered insights into how collaborators should set boundaries for foreground and side-ground/post-ground knowledge, blocking unintended knowledge spillovers during the partnership is a distinct challenge. Although formal access to IP can be blocked through a proper contract, knowledge spillovers can still occur. Future research should aim to address how collaborators can effectively avoid such circumstances, exploring routes that can track and prevent unintended knowledge spillovers.

Lastly, our analysis focuses on the production of technologies, representing an early phase of the innovation process. Future studies can extend the proposed perspective of measuring mutual learning to products and sales-related outcomes. Focusing on the market aspect would require a long-term approach but will help in the evaluation of outcomes by considering value capturing beyond value creation.

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Conflict of interest statement

The authors have read and understood the journal's policies on copyright, ethics, and conflicts of interest and believe that neither the manuscript nor the study violates any of these.

Data availability statement

The data that support the findings of this study are available from the corresponding author upon request.

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Notes

[1] The terminology is used by Bader (2007) and Granstrand and Holgersson (2014) (see Section 2 for details).

[2] The creation of co-patents and the allowance of mutual access to them are especially relevant in situations where inventions are in the open innovation space, such as creating a technology standard or highly complex new technologies (Gassmann et al., 2021).

[3] Although we narrowed the empirical focus due to data availability, our framework can still be conceptually useful and relevant in practice. A firm can keep monitoring its own unpublished and published capabilities and evaluate them based on what has been learned from the partnership.

[4] Later, BOSCH brought BMW as a customer for the partnership, instead of Volkswagen.

[5] In 2009, SB LiMotive acquired Cobasys, a US company specializing in battery pack. Following the dissolution of SB LiMotive, Cobasys was absorbed by BOSCH. During 2009–2012, a few patents (approximately 16 at the family level) were filed under the name of Cobasys, and some were later reassigned to Samsung SDI and BOSCH.

[6] The full model is not appropriate in this context because of the high negative correlation between the measures for exploitation and exploration, as expected by the definition.

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APPENDIX A

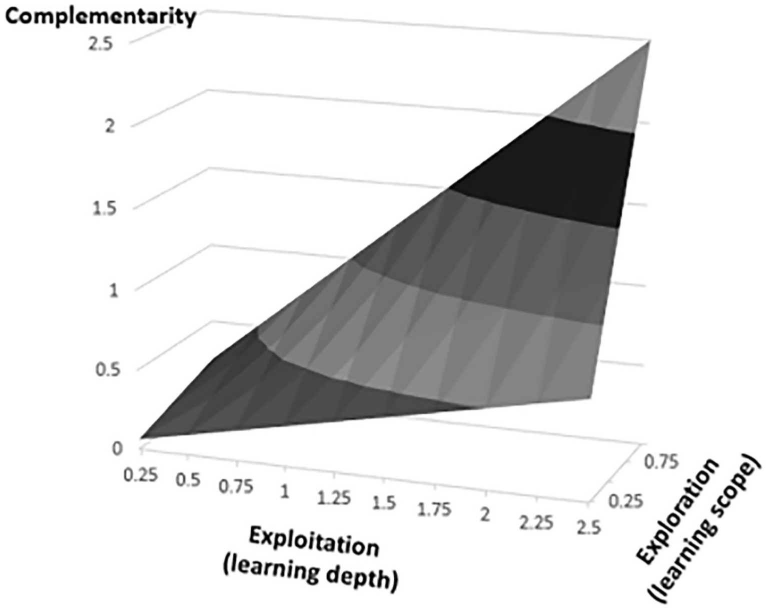

Figure A1. Distribution of complementarity. This figure illustrates that complementarity increases as both exploitation and exploration levels rise. The exploration level (learning scope) ranges from 0 to 1, while the exploitation level (learning depth) can take any value above 0. In our dataset, the maximum depth observed is 2.6.